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The Impact of Cobalt on Conflict – Evidence from the Democratic Republic of the Congo

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Abstract

Demand in cobalt has been surging in recent years due to advancements in technology and the requirements for batteries. Mining of minerals like cobalt is often associated with conflict. This paper investigates if cobalt can be related to conflict by replicating the work of Berman, et al. (2017) and finds mixed results. Thus, minerals are distinguished into labor- and capital-intensive ones, which yield findings similar to Dube and Vargas (2013). This is done through classification of main minerals and heterogeneous effects. The paper concludes that cobalt can be regarded a labor-intensive resource and therefore decreases the likelihood of conflict.

Keywords: Conflict, Mining, DRC, Congo, Cobalt

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List of Tables & Figures

1. Introduction

Battery powered devices are becoming an almost inevitable luxury in all parts of the world. While cellphone adoption is becoming stronger in the developing parts of the world, environmental considerations drive forward the market demand for electric vehicles in wealthier countries. What many of these devices have in common is a lithium-ion battery. A crucial ingredient to this type of battery is cobalt, which has seen strong increases in demand due to the afore mentioned developments and has ever rising demand projections. Most of this mineral is mined in the conflict prone Democratic Republic of Congo (DRC).

Given the relatively unstable political and socio-economic environment in the DRC, such stark changes in demand for cobalt can have severe consequences for the country. This work attempts to shed light on some of said consequences. Cobalt mining is often portrayed as exploiting local communities and workers, disregarding safety measures of miners, polluting the environment, fostering child labor and having a generally negative impact on Congolese miners. However, with rising prices it also has the potential to bring increased income to households and communities and thereby drive the economic development of local communities as well as the entire DRC. There is a widespread association among scholars between mining and conflict in respective areas, especially in resource rich sub-Saharan Africa. However, this topic is seldom formally discussed with regard to cobalt specifically. On one hand, rising prices could lead to increased opportunity costs of conflict. On the other, it could drive grievances and tensions among communities as well as artisanal miners and large mining operations. An interesting characteristic of cobalt is that it is extracted in different ways. While capital-intensive large-scale mines commonly extract cobalt as a by-product, labor-intensive artisanal mines contribute a significant portion to the minerals' total extraction volume. According to Dube and Vargas (2013), the impact of natural resources on conflict can be different depending on whether they are capital or resource intensive. Thus, this paper attempts to answer the question of what impact the price of cobalt has on the probability of conflict in mining regions.

To investigate this question, geo-coded historical data on conflict from the Armed Conflict and Event Data (ACLED) is analyzed. The dataset provides information on timing and locations of conflict as well as the involved parties and type of conflict. The latter information proves especially useful as it allows for a more granular interpretation of cobalt's impact on conflict. ACLED data is merged with observations on the locations of and main mineral produced by mines according to geo-referenced 0.5 x 0.5 degree (ca. 55 x 55 km) cells. The methodology applied follows closely the one of Berman, et al. (2017) but reveals somewhat different results. The crucial distinction is the more granular view provided as well as the application of a new mining dataset which includes cobalt and the focus on a single country.

Overall, this research finds a negative relationship between changes in the price of cobalt and the likelihood of conflict. While Berman et al. (2017) find an overall positive relation between changes in mineral prices and conflict, the work at hand shows that these results can differ when disaggregated by minerals and types of conflict. The results are distinguished into three types of conflict, battles, violence against civilians, and protests. Other than Berman et al. (2017), this work finds a significant negative relationship between cobalt prices and battles as well as protests. Although insignificant, the relationship to violence against civilians appears negative as well. Assuming that cobalt is largely sourced from labor-intensive artisanal mines, this relationship is in line with the opportunity cost mechanisms introduced by Dube and Vargas

(2013). The assumption is verified throughout this paper. This paper adds to the researchers work by showing that a resource does not need to be fully labor intensive to have negative impacts on conflict. Certain resourced can be extracted in either labor- or capital- intensive manners. What this paper shows is that if a large enough share of a resource is sourced in a labor-intensive manner the results of Dube and Vargas (2013) hold. To add validity to the presented results, the work of Berman, et al. (2017) is replicated for the DRC. Their results only hold to a certain extend in this context. Additionally, the results indicate that the opportunity cost and rapacity channels hold for artisanal and industrial mines, as these have different impacts on the likelihood of conflict.

The remainder of this paper is structured as follows. The next section provides a literature review of previously conducted research on the impacts of mining, its impact on conflict as well as the impacts of cobalt by itself. Further, arguments for the increasing importance of cobalt for the DRC are put forward. The third section describes the context of this study in more detail. More precisely, it points out the importance of cobalt for the DRC as well as the risk and history of conflict in the region. Data and respective sources are discussed in section four. While the baseline dataset is made available by Berman, et al. (2017) for replication of their results, the extension of cobalt required additional mining and price data. Also, a further dataset is employed to distinguish between capital and labor intensity of different minerals. Section five points out the implemented estimation strategy. It argues for the validity of prices as exogenous variables that can explain the relation between mining and conflict. In section six the results of the conducted analysis are presented. Interestingly, this work finds that the impact of mining can differ according to the type on conflict as well as the type of mining. The last section draws conclusions from the presented results.

2. Literature Review

It exists a wide array of academic work that focuses on the overall impact of mining on a variety of different measures in resource rich countries. These range from household consumption (Bazillier & Girard, 2019), poverty (Fisher, et al., 2009), corruption (Knutsen, et al., 2016) to conflict (Berman, et al., 2017, Dube & Vargas, 2013, Maystadt, et al. 2014). The last is where the work at hand positions itself.

Dube and Vargas (2013) develop a model that distinguishes capital- and labor-intensive resources and their respective impact on conflict. Their model is largely based on two opposing channels through which changes in resource prices may impact conflict, opportunity costs and rapacity. Generally, if a resource is labor intensive there are higher opportunity cost for engaging in conflict when the price for that resource increases. On the other hand, higher prices may make capital intensive resources more profitable and therefore more prone to appropriation by armed groups who use proceeds to finance their fighting. The latter is coined the rapacity effect. The focus on the mining industry allows the distinction of two extraction methods, large-scale mining (LSM) and small-scale and artisanal mining (ASM). These can be regarded as capital- and labor-intensive, respectively since LSM requires major up-front investments while ASM often makes use of rudimentary tools and techniques. The German Federal Institute for Geosciences and Natural Resources (BGR) finds that up to 20 percent of all cobalt extracted in the DRC is mined in small scale and artisanal mines (BGR, 2017). Potentially, this share of labor-intensive extraction is enough for the opportunity cost mechanism to work. On the other side, capital-intensive industrial large-scale mining is often criticized for embracing political formalizations that solidify state control, failing to reduce poverty and driving corruption, and thereby creating tensions that can lead to further conflict (Verweijen, 2017; Geenen and Cuvelier, 2019). This would support again the findings of Dube and Vargas (2013) in terms of the mining industry.

Berman, Couttenier, Rohner, and Thoenig (Berman et al., 2017) conduct a comprehensive study on the impact of mining activity on the likelihood of conflict for the entire African continent. They find a significant and generally positive relation between mining and the occurrence of conflict at the local level. In their work they argue that large parts of violence across African countries can be explained by rising mineral prices. An important mechanism in this regard is the feasibility effect. That is, a rise in mineral prices makes conflict more feasible, as resources appropriated by fighting groups become more profitable and thereby lower financial hurdles to fighting. The analytical framework of this paper follows closely the research conducted by Berman et al. (2017).

The existing literature on the economic, social and political of cobalt mining is plentiful. However, most of this work is qualitative and often lacks empirical evidence. Sovacool (2019) employs expert and community interviews as well as natural observations to investigate how cobalt is extracted as well as the risks and benefits of cobalt mining (Sovacool, 2019). Among other effects, the author points out the inherit risk of conflict that cobalt mining brings with it. Conflict is mostly inflicted by tensions either among communities when new mining cites are discovered and displacement occurs (World Bank, 2007) or between large scale mines and artisanal miners over concessions (Tsurukawa et al., 2011). Additionally, tensions occur due to corruption in the local mining-police, weak local governance or rent-seeking traders (Sovacool, 2019).

Some of these tensions are explored by Maystadt, et al. (2014) who analyze the impact of mining concessions on the number of conflicts in different spatial nuances and find mixed results (Maystadt, et al., 2014). According to them, mining concessions have no impact on conflict on a territory level, but foster conflict on a district level. Such spillover effects are a common finding in conflict literature and are therefore also included here. The authors construct a theoretical model in which entrepreneurs invest in the protection of their mining sites, lowering territorial conflicts, while grievances drive conflicts on a district level. These grievances can be related to the displacement of miners that occurs when new mining cites open in neighboring districts.

The demand for cobalt has been surging over the last decade. The rise of electric vehicles (EVs), the broader adoption and more frequent replacement of cellphones all contribute to this rising demand (Globalenergymetals.com, 2020). That is because all those afore mentioned are yet depended on lithium-ion batteries, which contain cobalt. Not only are these products becoming more popular and wider adopted, they also require ever increasing amounts of energy which in turn requires larger batteries (Reuters, 2020).

3. Context

While these advancements in technology have a wide array of benefits from reducing allegedly reducing the carbon footprints (EVs) to putting great computing power into the hands of a majority of consumers and even coordinating democracy movements, there are some downsides as well. Fast paced technological development makes technologies become outdated very quickly. In 2017 the global average replacement rate for smartphones was 21 months (Counterpoint, 2017). Not only does this produce large amounts of electronic waste, but it drastically increases the demand for minerals like cobalt, that are more often than not extracted under conditions unimaginable to the end-users of such products.

To put into context the importance of cobalt mining and conflict in the DRC is elaborated next. Cobalt mining in the DRC dates back to the times of Belgian colonization (Honke, 2010). In the decades following the country's independence, cobalt mining was largely monopolized by state owned Gécamines (Al Barazi et al., 2017). During the first Congolese war between 1996 and 1997, cobalt mines were expropriated by rebel forces, in order to gain international support in their pursuits against the Mobutu regime. After accomplishing this goal, the new government led by Laurent Desire Kabila faced militant forces from neighboring countries, trying to overthrow his government once again in the second Congolese war from 1998 to 2003 (Amnesty International, 2016a). The raging chaos left Gécamines largely inoperable giving rise to artisanal mining operations which from 1999 gained recognition by the national government as means to generate income in terms of income taxes from miners and mining companies as well as the issuing of mining permits. Despite later efforts to attract international investment and thereby driving artisanal miners out of their territories, an estimated 20 percent of Congolese cobalt is mined in artisanal mines (BGR, 2017).

With rising demand for cobalt in electronic goods, the DRC is gaining importance as the world's top supplier of the mineral. Roughly 60 percent of cobalt are mined in the DRC (Reuters, 2018). While such a position might at first seem promising to the developing country's economic success, it might inherit some social costs. In the race to secure deposits and gaining access to the countries limited extraction capacity, conflict is prone to develop. This conflict could be between rivaling firms as well as among the population. Reasons for civil conflict in this context are plentiful. First, local populations might fear the expropriation of land through foreign companies and investors, who extract the lands riches without benefiting local communities appropriately. Second, these grievances might not only be directed at the companies themselves but also towards political parties as local communities might perceive outside investments as "selling out their land". Third, conflict might be driven by the lootability of artisanal mines. With rising prices, certain groups might be more inclined to forcefully gain access to mining sites or storage depots.

The large share in worldwide cobalt production, frequent violent events, relatively unstable institutions and low prosperity for Congolese citizens make the DRC a prime subject in the analysis of cobalt's impact on conflict. Artisanal mining is often subject to little oversight in terms safe practices or protection from extortion. Additionally, the lack of domestic capital in the DRC requires outside investments making the country subject to potential exploitation and according grievances.

4. Data

The data used in this analysis builds on the data framework of Berman et al. (2017). The researchers combine conflict data from the Armed Conflict and Event Data Project (ACLED) with mining data from Raw Material Data (RMD) as well as price data from the World Bank on the basis of the Peace Research Institute Oslo's (PRIO) gridded location data. This paper extends the dataset by adding mining data and respective prices. To do so, some additional datasets were employed for mines, prices and mining characteristics. Simultaneously, the dataset was reduced to include only observations regarding the DRC. The specifics of each dataset are discussed below.

Conflict data – ACLED distinguishes types of conflicts according to reports and does therefore not solely rely on proxies such as a threshold on casualties. These events include violence (political or non-political), protests as well as non-violent events by political agents. The distinction between types of conflict is important to this paper because, as it turns out, cobalt mining has different effects of different kinds of conflict. A main channel for this is that different kinds of conflicts are initiated by different political actors (i.e. government forces, civilians protesting, terrorist groups).

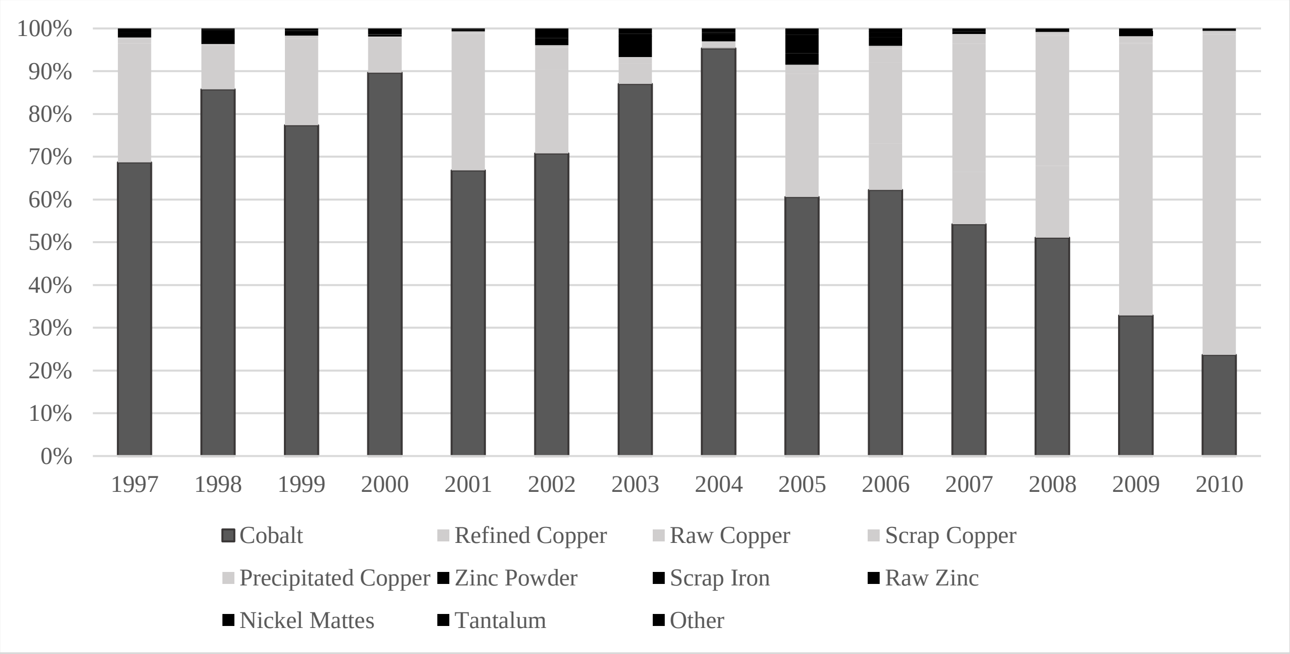
Location data is referenced using a 0,5 × 0,5 degree (55 × 55 km) grid as provided by the Peace Research Institute Oslo (Tollefsen, Strand & Buhaug, 2012). To ease the analysis of this enormous panel dataset a dummy variable is created that is one if at any time during a given year conflict occurred in a respective cell. This allows to analyze the impact of mining on conflict while ignoring the dynamics of conflict onset. If conflict is already appearing, a change in minerals prices is unlikely to have a particular impact on its onset.

The way ACLED collects data might create a bias towards certain countries, regions or events with better media coverage (Berman et al., 2017). By focusing on only one country much of this bias is ruled out. Some small chance remains that events in rural areas are reported less frequently or accurately. However, since most mining operations are located in specific rural areas, media coverage can be assumed to be equivalent throughout mining regions and does therefore not disturb results. This smaller dataset reduces overall heterogeneity compared to that of Berman et al. (2017).

Raw Material Data – Berman et al. (2017) use data from IntierraRMG which contains the location, minerals produced, total production as well as the start of production and current activity. The most important variable extracted from this dataset is a dummy variable that is one if at least one mine is active in a specific cell during a given year. In addition, the researchers identify one of 14 minerals as the main mineral of a cell. The main mineral is defined as the most produced mineral over the entire period of observation. The number of included minerals is limited by the availability of price data in the World Bank's commodity price databank employed by the researchers. Berman at al. (2017) identify that 70 percent of the mining cells they identify produce a single mineral and 96 of production value stems from the identified main minerals. It is important to note however, that this applies to the whole of the African continent. Since the work at hand focuses on only a single country, there might be some difference in the relative importance of certain minerals. In the case of the DRC, cobalt becomes an important mineral that is excluded in the work of Berman at al. (2017). Figure 1 below shows the export value of cobalt from the DRC relative to other metals for the entire observation period.

Additionally, the researchers established a set of proxies to create interaction terms for capital intensive mining. The distinction between capital- and labor-intensive mining is crucial to the arguments made in this paper. Accordingly, a further proxy was introduced using information on artisanal and industrial mining taken from Global Forest Watch. The dataset is described in more derail later.

Figure 1 – Metal exports from the DRC between 1997 and 2010.



Source: Observation of Economic Complexity. The export value of all metals from the DRC is represented as a share of total metal export value in a given year. It is apparent that cobalt is of extraordinary importance for the Congolese metal industry. (https://oec.world/en/visualize/stacked/hs92/export/cod/all/show/1997.2010/)

A concern that Berman at al. (2017) point out about IntierraRMG dataset is that it only includes mines operated by major companies and could therefore lead to some "*attenuation bias*". This concern might be even more valid given the smaller sample. However, mines can be assumed to be spatially clustered and therefore small mines are likely to be included in the employed mining dummy. The IPIS dataset used to supplement the original mining data has a focus on small and artisanal mines and therefore contributes to eradicate the concern of potential exclusion of small mines. The specifics of IPIS data are discussed next.

Cobalt data – is sourced from the International Peace Information Service (IPIS). IPIS is an independent research institute providing a variety of development data (IPIS, 2020). As such, one of their projects focuses on the mapping of artisanal and small-scale mining in the eastern DRC (IPIS, 2010). Here they provide information on the exact location (latitude and longitude) of the mines as well as primary, secondary and tertiary minerals mined. Data on latitude and longitude is easily linked to PRIO grid cells. The data on the extracted minerals is then used to construct a dummy variable for the extraction of cobalt in a respective grid. The IPIS data is used to complement the original dataset of Berman et al. (2017) and represents the main contribution of this work in terms of data.

A major drawback of this dataset is that it does not give any detailed information on the activity of mines, i.e. whether a mine is operational or not. One way to adjust for this is to only add the information on main minerals to Berman et al.'s (2017) dataset where the presence of mines does not change over the observed time period (SD(mines) = 0). Another way is to assume that the mines from the IPIS dataset are open during the entire period from 1997 to 2010. The impact of this on the accuracy of the dataset is negligible as changes the standard deviation of mines from 0,116 to 0,114. Since the latter approach yields more observations on mining it is employed throughout this work.

Mining concessions – Global Forest Watch provides a dataset of mining concessions which is sourced from the Congolese Ministry of Mines Mining Registry (CAMI). While the original dataset is only available for purchase, the abstracts used by Global Forest Watch are freely available. The data was used mainly in the construction of Table 3 and the distinction between capital- and labor-intensive mining. Congolese mining authorities distinguish between the methods used in mining when providing permits. This allows to analyze which minerals have a greater share in artisanal, small scale and industrial mining relative to other minerals. A precise overview is provided in the appendix (Table A2). Given that the arguments on conflict mechanisms made here rely strongly on the distinction between capital- and labor-intensive mining, this data provides a better proxy than the one employed by Berman et al. (2017).

Minerals Prices – Berman at al. (2017) use World Bank commodity prices at real 2005 US$ as price for the minerals included. While there is little to question about the quality and applicability of the data, it is limited to 14 of the observed main minerals. The researchers complement World Bank prices with data from Rapaport and the US Geological Survey (USGS) for diamonds and tantalum, respectively. Diamond and tantalum prices are not included in the World Bank commodity prices and the USGS provides US unit values rather than world prices. In the baseline model applied by Berman et al. (2017), diamonds and tantalum are hence excluded. The researchers show that adding these observations does not strongly affect their results. However, given the smaller, more focused dataset applied in this study, diamonds and tantalum change the outcomes significantly. Therefore, these minerals are included in the analysis at hand.

Cobalt Prices – While the World Bank's commodity "pink sheet" provides yearly prices for most of the considered minerals, some prices needed to be sourced elsewhere. A similar approach was taken by Berman at al. (2017) for the price of tantalum and diamonds. The United States Geological Survey (USGS) provides an extensive list of yearly observations of mineral prices. From this list the prices of cobalt, tantalum and manganese were taken. The real prices in this dataset are in constant 1992 US$, which is different from the World Bank prices used by Berman at al. (2017) (2005 US$). However, the USGS provides the price deflators used in the calculation of real prices, which allows to reverse engineer the real prices from this dataset to fit the one of Berman at al. (2017).

5. Estimation Strategy

A major problem in estimating the impact of mining on conflict is potential reverse causation. It is possible that mines cause conflict, however conflict can also have an impact on the activity of mines (miners might engage in conflict rather than resuming mining or larger mine activities might be affected in other ways). A distinction between these effects can be made by the direction of the correlation. If mines cause conflict one would expect a positive correlation between the two and vice versa for the case of conflict affecting mining activity. However, Dube and Vargas (2013) argue that different resources can have different impact on conflict, depending on whether a resource is labor or capital intensive in its production. Mining can take both forms. Certain minerals are easily extracted from the ground using rudimentary tools such as pickaxes and shovels and can thus be considered labor-intensive. Others require the deeper explorations in the form of mining shafts or extremely costly large-scale open mining casts; hence they are capital-intensive. Furthermore, certain minerals might only be profitable if mined in large quantities that require high degrees of automation. Table 3 shows that there are distinctions between both types of mining and their impact on conflict.

Berman et al. (2017) address causation by focusing on exogeneous variations in the value of mines. This value is determined as the value of the main mineral sourced in a specific cell. The researcher's pursuit the idea that rent seeking increases the likelihood of violence and that it is large for more valuable mines. Conveniently, world prices of minerals are mainly determined by the demand and are therefore exogeneous. In the case of cobalt in the DRC this exogeneity is challenged since close to 60 percent of world supply stem from this country. However, it is unlikely that conflicts in one particular grid cell in the DRC will impact the world price of cobalt (Maystadt, et al., 2014). Hence the main specification of the model at hand takes the following form:

$$(1)\ Conflict_{jkt} = \alpha_1(M_{kt} \times \ln p_{kt}^{W}) + \alpha_2(C_{kt} \times \ln p_{kt}^{W}) + \boldsymbol{FE}_k + \boldsymbol{FE}_t + \varepsilon_{kt},$$

Where (k, t, j) represent cell, time, and the type of conflict, respectively. $\boldsymbol{FE}_k$ and $\boldsymbol{FE}_t$ describe cell and year fixed effects. M_{kt} is the described dummy variable that takes the value of one if at least one mine is active in a cell during a given year. C_{kt} is another dummy variable that is one if cobalt is mined in a cell. Finally, p_{kt}^{W} describes the world price of cell k's main mineral during year t. The reason why only interaction terms are included is the M_{kt} is either zero or one for the entire sample and is absorbed by the fixed effects when not included in the interaction term. Further, the covariates of $\ln p_{kt}^{W}$ and the interaction term become identical. α_2 is the main coefficient of interest, as it represents the impact of a change in cobalt price on the likelihood conflict.

Causality is established in several ways. First, α_1 is determined under the condition of mines being open during the entire observation period (SD(mines) = 0). This controls for the effects that conflict can have on mining activity (opening/closing). Second, by including cell fixed effects, time invariant co-determinants of mining and conflict, such as political instability or inefficient enforcement of property rights are controlled for in each observed cell. Third, year fixed effects serve the same purpose for time variant factors such as war.

An important notion that the ACLED dataset allows to control for is that the types of conflict might vary depending on who engages in conflicts. Governments can use force against civilians while civilians may protest or form anti-governmental militant (terrorist) groups. Typically, the triggers for such conflicts will differ depending on the source of conflict. Terrorist attacks are likely to be differently motivated than civil protests. Given these differences in the source of conflict one can argue that (different types of) mining can have different impact on different kinds of conflict. In the work at hand, the events reported by ACLED are divided into three categories, battles, violence against civilians and protests. The last one includes riots. In the case of cobalt, being a labor-intensive mineral, one expects grievances to be larger if major companies misappropriate land or are perceived to exploit local citizens. On the other hand, governments are likely to be in support of large companies investing into their economy. From this, one could expect the presence of a major company to increase the likelihood of protest as well as violence against civilians. The feasibility mechanism and the easy access to ASMs would argue for a positive relationship between battles and cobalt mining.

6. Results

The first step in the analysis of cobalt mining on violence is to replicate the work of Berman et al. (2017) for the subsample of the DRC. Their original work finds positive correlations between mining and the likelihood of conflict for the whole of Africa. Table 1 presents the results for the DRC.

Table 1 – Replicating Berman et al. for DRC only.

	Battles		*Violence against civilians*		*Riots / Protests*	
	Within Cell	*Spillovers*	*Within Cell*	*Spillovers*	*Within Cell*	*Spillovers*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
ln price mainmineral	-0,182*		-0,031		0,041	
	(0,104)		(0,033)		(0,036)	
ln price × mines >0	0,192**	-0,018	-0,021*	-0,083**	-0,023	0,041
	(0,096)	(0,021)	(0,036)	(0,035)	(0,052)	(0,035)
ln avg cell price × mines >0	-0,173**		-0,034		0,039	
	(0,083)		(0,037)		(0,063)	
ln prices × mines in		0,054**		0,071*		-0,002
Neighboring cells		(0,023)		(0,037)		(0,004)
Observations	10.640	9.646	10.640	9.646	10.640	9.646

Notes: * - p < 0.1; ** - p < 0.05; *** - p < 0.01. LPM estimations. Conley (1999) standard errors in parentheses, allowing for spatial correlation in a 100km radius and infinite serial correlation. All estimations include year and cell fixed effects. Variables: *mines > 0* is a dummy variable that is 1 if a mine was observed at some point during the observation period and 0 otherwise; *ln price mainmineral* is the natural log price of the mineral with the highest production over the observation period for each mining cell at real 1997 prices and is zero for non-mining cells; *ln avg cell price* is the natural log average price for a cells main mineral at real 1997 prices during the observation period; mines in neighboring cells is a dummy variable that is 1 if mines are observed in any of the neighboring cells of degree 1 and 2.

The results are split across the three different types of violent events and limited to observation from the DRC. The table shows that a variation in the price of a mineral have a significant impact on the likelihood of battles (column 1) and violence against civilians (column 3). While the results for battles are in line with the original work, the results for violence against civilians and protests paint a different picture. These results are obtained from the observation of those mining cells that were active during the entire observation period (SD(mines) = 0). Interestingly, mining does not seem to significantly affect civilian uprise (riots/protests). A possible explanation for these non-significant results are opportunity costs that miners face when engaging in protests instead of engaging in mining activity. This interpretation explains to a certain extent the negative correlation between violence against civilians and mining. Without civil unrest there is no need for government forces to intervene. An alternative interpretation is that the likelihood of violence against civilians is lower in mining areas compared to non-mining areas. This can be explained by possible grievances and/or lower opportunity costs in said areas. Column 2, 3 and 4 show potential spillover effects from mines in neighboring cells. Spillovers are significant and positive for both, battles and violence against civilians. The coefficients for spillover effects are generally lower compared to within cell effects indicating that the source of conflict is largely caused by forces within those cells. This positive correlation might be driven by forceful appropriation of land, as argued for by the feasibility and rapacity effect.

Table 2 below shows that cobalt mining in itself is a strong determinant for the likelihood of conflict in the respective mining areas. Contrary to Berman et al. (2017) cobalt mining is found to have an overall negative impact on conflict. This table represents the main results of this paper.

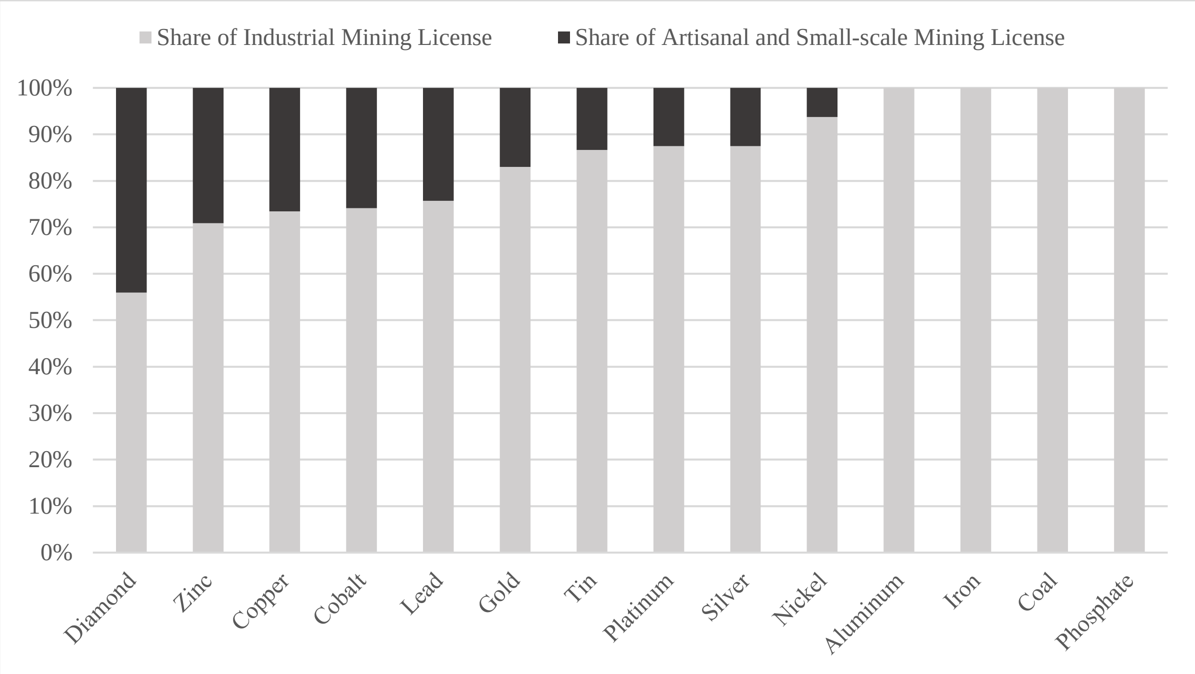
Table 2 – Impact of cobalt mining on conflict.			
	Battles	*Violence against civilians*	*Riots / Protests*
	(1)	*(2)*	*(3)*
ln price × mines >0	0,025	-0,029	0,036
	(0,025)	(0,020)	(0,037)
Cobalt × lprice	-0,090*	-0,049	-0,014**
	(0,054)	(0,035)	(0,006)
Observations	10.556	10.556	10.556

Notes: * - p < 0.1; ** - p < 0.05; *** - p < 0.01. LPM estimations. Conley (1999) standard errors in parentheses, allowing for spatial correlation in a 100km radius and infinite serial correlation. All estimations include year and cell fixed effects. Variables: *mines > 0* is a dummy variable that is 1 if a mine was observed at some point during the observation period and 0 otherwise; *ln price* is the natural log price of the mineral with the highest production over the observation period for each mining cell at real 1997 prices and is zero for non-mining cells; *Cobalt* is a dummy variable that is 1 if cobalt is mined in a cell at any point over the observation period.

While the results for the cobalt interaction term are all negative (as expected for minerals mined in ASMs) only results for battles and protests are significant. A possible reason why violence against civilians does not show significance are incidence involving the mining police (Sovacool, 2019). These are likely to disturb the otherwise negative relationship between cobalt mining and conflict. One can argue that the opportunity costs argument of Dube and Vargas (2013) holds for battles and protests. With an increase in the prices of cobalt, miners would miss out on greater profits from their work by not mining. Thus, they will prefer to engage in mining cobalt rather than engaging in protests or joining armed forces against the government which reduces incidence. However, for this argument to hold cobalt would need to be a labor-intensive resource. This paper argues that the distinction between labor- and capital-intensive minerals can be made by its most prevalent mining type. ASM can be considered as labor-intensive and LSM as capital-intensive. Figure 2 provides an overview of which minerals are more frequently mined under ASM or industrial mining permits. Data was extracted from the

Global Forest Watch dataset, that lists mining permits and the respective minerals mined. The illustration shows that cobalt at roughly 26 percent, together with lead (24 percent), copper (26 percent), zinc (29 percent) and diamonds (44 percent) is extracted in ASMs relatively more often than other minerals.

Figure 2: Share of ASM permits by mineral.



Source: Global Forest Watch. The figure represents the relative frequency of mining permits under which specific minerals are mined.

If the framework of opportunity costs and rapacity effects of Dube and Vargas (2013) applies to artisanal and industrial mining, one can expect different results from both types in terms of their respective impact of conflict. To investigate this, two dummy variables were constructed that are one if a mineral could be considered to be mined either using ASM or LSM and zero otherwise. Mines extracting minerals that are defined as ASM operate under artisanal, tailing or small-scale mining permits in at least 26 percent (copper) of all mining permits recorded by the National Forest Watch dataset. LSM minerals are mined under industrial permits in at least 82 percent (gold) of cases (Note: most of the considered industrial minerals are mined exclusively under large-scale permits). Cobalt is excluded from this analysis, to show that it is not the main driver of these effects. Table 3 shows the results for impacts of industrial and artisanal mining on the battles, violence against civilians and protests, respectively.

Table 3 – Impact of mining types on different types of conflict.

	Battles	*Violence*	*Protests*
	(1)	*(2)*	*(3)*
ln price × industrial	0,027***	-0,016***	0,001
	(0,006)	(0,006)	(0,002)
ln price × artisanal	0,008	-0,039*	0,037
	(0,022)	(0,022)	(0,038)
Test for equality of coefficients	0,141	0,020**	0,321
Observations	10.584	10.584	10.584

Notes: * - p < 0.1; ** - p < 0.05; *** - p < 0.01. LPM estimations. Conley (1999) standard errors in parentheses, allowing for spatial correlation in a 100km radius and infinite serial correlation. All estimations include year and cell fixed effects. Variables: *mines > 0* is a dummy variable that is 1 if a mine was observed at some point during the observation period and 0 otherwise; *ln price* is the natural log price of the mineral with the highest production over the observation period for each mining cell at real 1997 prices and is zero for non-mining cells; *industrial* is a dummy variable with value 1 is the main mineral of a cell is mined under industrial mining permits at least 82% of cases and 0 otherwise; *artisanal* is a dummy variable that is 1 if a cells main mineral is mined under artisanal, small-scale or tailings permits in at least 26% of all cases and 0 otherwise. The equality of coefficients is tested using a Wald-test for equivalence of hypotheses.

As presented in columns 1 and 2 of table 3, there are significant correlations for different types of mining and conflict. While industrial (capital intensive) mining has a significant and positive effect on battles, there are no significant effects of artisanal (labor intensive) mining (column 1). For violence in column 2, both industrial and artisanal mining have negative and significant effects. However, the effect of artisanal mining is significantly stronger ($p < 0,05$) than that of industrial mining. Both effects follow the argumentation of Dube and Vargas (2013), that labor-intensive resources lower the likelihood of conflict by increasing opportunity costs.

To support these results some proxies for artisanal and industrial mining are evaluated in Table 4. Following Dube and Vargas (2013), one should expect opposite effects of industrial and ASM operations on conflict, where industrial mining proxies will increase the likelihood of conflict while the opposite should be true for ASM proxies. Some of these proxies are elaborated upon in table A1 in the appendix.

Table 4 – Impact of artisanal mining proxies on conflict.

	Battles		Violence		Riots	
	(1)	(2)	(4)	(5)	(7)	(8)
ln price × mines >0	0,024***	0,023	-0,011**	-0,001	0,000	-0,001
	(0,006)	(0,034)	(0,005)	(0,005)	(0,001)	(0,004)
× above avg luminosity	-0,071*		-0,058		-0,009**	
	(0,041)		(0,049)		(0,005)	
× Major company		0,011		0,386***		0,642***
		(0,056)		(0,035)		(0,030)
Observations	10.570	182	10.570	182	10.570	182

Notes: * - p < 0.1; ** - p < 0.05; *** - p < 0.01. LPM estimations. Conley (1999) standard errors in parentheses, allowing for spatial correlation in a 100km radius and infinite serial correlation. All estimations include year and cell fixed effects. Variables: *mines > 0* is a dummy variable that is 1 if a mine was observed at some point during the observation period and 0 otherwise; *ln price* is the natural log price of the mineral with the highest production over the observation period for each mining cell at real 1997 prices and is zero for non-mining cells; *above avg luminosity* is a dummy variable that is 1 if nightly light emission in a cell is higher than average in the DRC and 0 otherwise; *Major company* is a dummy variable that is 1 if a company that is among the top 10 producers of the main mineral is present in a mining cell and 0 otherwise. The explanatory value of *above avg luminosity* and *Major company* is elaborated in Table A1.

Average luminosity is amount of nightly light emission as a yearly average for a given cell. Generally, luminosity is a good indicator for population density as well as access to electricity. Here, average luminosity has some predictive power for the likelihood of a mineral being mined artisanal or industrial as shown by table A1. The correlation is positive for artisanal mines and slightly negative for industrial mines. This is intuitive as highly automated mines require less labor and will therefore not attract surrounding communities. At the same time, these mines might force mining communities out of a given cell when opened, as mining grounds might be “taken away” by the operators of large-scale mines. Artisanal mining on the other hand is fostering the creation of communities. ASMs are typically welcoming newcomers (Bazillier & Girard, 2019) are thereby provide good job opportunities (mostly for young men). In addition, these mining communities will benefit from proximity to their mining sights, driving up the correlation between luminosity and small scale mining.

The share of the main mineral in the total production in a cell is negatively related to the likelihood of a mine being artisanal. Likely this is caused by the de-centralized character of artisanal mines. ASM miners might either individually specialize in certain minerals or extract a broader array of minerals, all of which represent some value. Large scale mines on the other hand might have a greater focus on singular minerals for which their machinery is specialized.

Presence of a large company increases the likelihood of a mineral being mined by ASMs. This is likely explained by lower costs of entry for artisanal miners. Specifically, the presence of a large mining company allows miners to sell extracted minerals more easily. Large distance to mining companies requires means of transportation for extracted goods which might go along with higher capital intensity. Even if a logistical network is in place, it is likely that ASMs in proximity to major companies are serviced more frequently and easily. A further explanation could be that major mining companies focus on regions in which minerals are abundant and easily accessed, which also eases market entry for artisanal miners.

As shown in column 1, above average luminosity is negatively correlated with the likelihood of battles. This is in line with the observations in table A1 as well as the concepts of Dube and Vargas (2013). Above average luminosity is an indicator of ASM operations, which are expected be negatively correlated with the likelihood of conflict.

Columns 2, 5 and 8 show the effects of the presence of a major company in a mining cell for battles, violence against civilians and protests, respectively. Strong significant effect can be seen in columns 5 and 8. In the logic of Dube and Vargas (2013) and in light of table 3 this appears counterintuitive. Since in table A1 the presence of a major company has a positive impact on the likelihood that a mineral is mined in ASMs, one would expect this factor to be negatively correlated with conflict. However, grievance due to perceived expropriation of land and the employment of mining police are likely to be stronger in the presence of major companies and to spark riots and violence against civilians, respectively (Sovacool, 2019).

7. Conclusion

This work analyzed the impact of cobalt mining on conflict in the mining regions within the DRC. With rising demand for cobalt due to faster development in technologies, especially batteries, cobalt is experiencing large spikes in price. Mining is widely considered to be a driving force of conflict, especially when combined with weak institutions as often seen in Sub-Saharan Africa. The question this paper investigates is how fluctuations in prices of cobalt impact conflicts. To do so, it borrowed data from Berman et al. (2017) as well as concepts from Dube and Vargas (2013) to estimate the likelihood of different types of conflicts for changes in the price of cobalt. In several steps it was validated that the works of Berman et al. (2017) only partially hold for the sub-sample of the DRC and for specific minerals that are known to be mined on an either large-scale or ASM basis. Since cobalt is often found to be mined in ASMs, according to Dube and Vargas (2013) one should expect a price increase to reduce the likelihood of conflict in mining regions. The presented results show an overall negative impact of cobalt mining on conflict. This holds true for two distinct types of conflicts, battles and protests. It is easy to argue that, especially for these types of conflict the opportunity costs mechanism holds. Nonetheless, results were insignificant for violence against civilians, which is likely an indication of weak policy measures towards the regulation of mining as well as corruption in mining regions. Implications of the presented results include the encouragement of artisanal mining in the DRC, through easier access to mining permits as well as sound control, enforcement, and taxation mechanisms.

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Appendix

Table A1 - Differences between artisanal and industrial mined minerals

	Artisanal *(1)*	*Industrial* *(2)*
Average cell luminosity	0,122***	-0,051***
	(0,015)	(0,006)
Share of main mineral	-0,587*	
	(0,302)	
Major company	0,326***	
	(0,058)	
Observations	2.370	2.370

Notes: * - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$. LPM estimations. Conley (1999) standard errors in parentheses, allowing for spatial correlation in a 100km radius and infinite serial correlation. All estimations include year and cell fixed effects. Variables: *industrial* is a dummy variable with value 1 is the main mineral of a cell is mined under industrial mining permits at least 82% of cases and 0 otherwise; *artisanal* is a dummy variable that is 1 if a cells main mineral is mined under artisanal, small-scale or tailings permits in at least 26% of all cases and 0 otherwise; *above avg luminosity* is a dummy variable that is 1 if nightly light emission in a cell is higher than average in the DRC and 0 otherwise; *Share of main mineral* is the share that the main mineral contributes to the total mining production of a mining cell in year t. *Major company* is a dummy variable that is 1 if a company that is among the top 10 producers of the main mineral is present in a mining cell and 0 otherwise;

Table A2 – Mining permits by mineral

		ASM		
Mineral	Industrial mining license	Small-scale Exploitation Permit	Tailings Processing Permit	Artisanal Exploitation Area
Copper	73,42%	16,03%	8,44%	2,11%
Aluminum	100,00%	0,00%	0,00%	0,00%
Lead	75,68%	16,22%	8,11%	0,00%
Tin	86,67%	13,33%	0,00%	0,00%
Nickel	93,75%	6,25%	0,00%	0,00%
Zinc	70,91%	23,64%	5,45%	0,00%
Gold	82,98%	16,60%	0,43%	0,00%
Platinum	87,50%	9,38%	3,13%	0,00%
Silver	87,50%	8,65%	3,85%	0,00%
Iron	100,00%	0,00%	0,00%	0,00%
Coal	100,00%	0,00%	0,00%	0,00%
Phosphate	100,00%	0,00%	0,00%	0,00%
Diamond	55,93%	39,55%	0,00%	4,52%
Cobalt	74,14%	15,52%	8,19%	2,16%

Source: Global Forest Watch